NOTES 10: SAMPLING DISTRIBUTIONS

Stat 120 | Fall 2025

Prof Amanda Luby

"Big picture" picture:

Quantity	Statistic	Parameter
Mean		
Proportion		
Standard Deviation		
Correlation		
Regression Coefficient		

Carleton publishes an "at a glance" page with some facts and figures about the student body: https://www.carleton.edu/about/carleton-at-a-glance/

Some highlights:

- Geographic distribution:
  - Midwest 36.7%
  - West 21.7%
  - East 17.3%
  - South 10.9%
  - International 11.8%
  - Other 1.6%
- 34% BIPOC
- 12% are among the first generation in their families to attend college
- 61% graduated in the top 10% of their high school class

In a moment, we're going to see one of these quantities for our class. Before we do, what is your *best guess* for each of these quantities?

Example: In this set-up, what is the:

- Population
- Sample
- Parameter

- Statistic

We know that our class will likely not have **exactly** 36.7% from the Midwest, but we probably wouldn't expect it to be 0% or 90%.

Sampling variability

We might start to ask ourselves, what if a *different* set of 32 students enrolled in this course?

First, we create a population.

```
# A tibble: 2,007 x 2
   student_id midwest
        <int> <chr>
 1        193 Yes
 2       1062 No
 3        111 Yes
 4       1111 No
 5        533 Yes
 6       1686 No
 7       1776 No
 8       1224 No
 9        877 No
10        338 Yes
# i 1,997 more rows
```

Then, we take a random sample:

```
set.seed(100424)
sample1 <- carls |>
  sample_n(32)
sample1
```

```
# A tibble: 32 x 2
   student_id midwest
        <int> <chr>
 1       1259 No
 2        826 No
 3        858 No
 4       1905 No
 5         40 Yes
 6       1336 No
 7       1607 No
 8       1757 No
```

```
 9        489 Yes
10        445 Yes
# i 22 more rows
```

and calculate the proportion of “yes” responses:

```
sample1 |>
  group_by(midwest) |>
  summarize(
    n = n()
  ) |>
  mutate(p_hat = n/sum(n))
```

```
# A tibble: 2 x 3
  midwest     n p_hat
  <chr>   <int> <dbl>
1 No         23 0.719
2 Yes         9 0.281
```

This isn’t *super* useful, but if we do it a bunch of times, we can start to see what a range of possible samples could look like. (*Note:* this code requires the {`infer`} package)

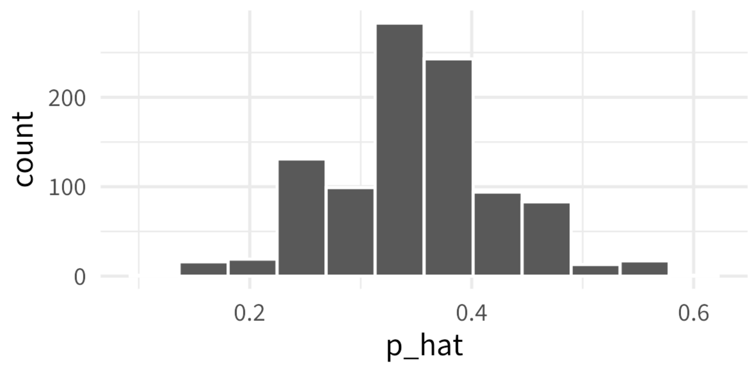
```
many_samples <- carls |>
  rep_sample_n(35, reps = 1000, replace = TRUE) |>
  group_by(replicate, midwest) |>
  summarize(
    n = n()
  ) |>
  mutate(p_hat = n/sum(n)) |>
  filter(midwest == "Yes")

many_samples
```

```
# A tibble: 1,000 x 4
# Groups:   replicate [1,000]
   replicate midwest     n p_hat
       <int> <chr>   <int> <dbl>
 1         1 Yes        12 0.343
 2         2 Yes         8 0.229
 3         3 Yes        15 0.429
 4         4 Yes        16 0.457
 5         5 Yes        15 0.429
 6         6 Yes        16 0.457
 7         7 Yes        16 0.457
 8         8 Yes        17 0.486
 9         9 Yes        15 0.429
```

```
10        10 Yes        10 0.286
# ℹ 990 more rows
```

Looking at this first few rows, we can start to get a sense of the range of possible sample proportions, but there are 990 rows that we can't see. Let's make a graph!



Example: Carleton Mission Statement

In your own words: provide explanations for:

Population distribution

Sample distribution

Sampling distribution